IMPROVEMENT OF LOW – CONTRAST MEDICAL IMAGE ANALYSIS SENSITIVENESS AND EXACTNESS USING MARKOV RANDOM FIELD MULTIDIMENSIONAL SEGMENTATION METHOD

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Abstract

In this work algorithm of medical images visual properties improvement for image analysis simplification was realized. The exactness and sensitiveness increasing of different image objects detection is achieved via gradient correction and segmentation. Pixels classification proceeds using Markov random field (MRF) conception. In order to increase the input segmentation data the multiresolution Wavelet decomposition method was proposed to take in consideration the information about more coarse region forms and borders. Using a number of "approximation" images generated by Wavelet transform together with the initial image allows us to make the resulting clusterisation more exact.

1. INTRODUCTION

In the area of medical images processing the resulting inaccuracy is usually conditioned by both the absence of sufficient input data amount and weak photos contrast. Accurate definition of weak contrast regions is more convenient to be accomplished with any image segmentation (clusterisation) methods. There are two different segmentation ways: "unsupervised" and "supervised". The obvious weakness of supervised algorithms such as K – means method or fuzzy C – means method [1],[2],[4] often lies in the absence of knowledge about true number of image objects, which must be detected. Due to this problem we used unsupervised clusterisation method. Moreover, during the segmentation process local spatial image characteristics of MRF model were taken into account what allows us to consider the input image not only as a simple set of different brightness pixels but also as a complex textured object.

Lets consider some gray – scaled image $Y=\{y_s\}$, where s is a pixel characterized by its coordinates: $s=(i,j)$, $i\in\{1..N\}$, $j\in\{1..M\}$, y_S is a gray level of s. The segmented version of Y is $X=\{x_s\}$; $x_s=k$ means that pixel s can belong to the segmentation class k.

The most known pixels classification method for the segmentation process is the maximization of a posteriori probability (MAP), which is usually defined by Bayesian relationship:

$$P(X \mid Y) = P(Y \mid X) \cdot P(X) \tag{1}$$

$P(X)\sim p(x_s=k)$ is a priori probability of pixel s belonging to segmentation class k, $P(Y|X)\sim p(y_s=y|x_s=k)$ is a conditional distribution of pixels intensity within certain class k. Both a priori and a posteriori probabilities are defined with respect to MRF model.

2. GAUSSIAN MARKOV RANDOM FIELD MODEL

Let an image Y be modeled on a finite lattice L by Gaussian Markov random field (GMRF) where $Y=\{y_{ij}: 0\le i\le M,\ 0\le j\le N\}$ and $L=\{(i,j): 0\le i\le M, 0\le j\le N\}$. A neighborhood system η_s is a set of all the pixels which are the nearest neighbors of pixel s. η_s must satisfy the following requires:

- s is not an element of η_s;
- if $k \in \eta_s$, then s should be an element of η_k.

The joint probability distribution of pixel brightness values is:

$$P(y) = \frac{1}{(2\cdot\pi)^{M\cdot N/2}(\det\Sigma)^{1/2}} \cdot e^{-\frac{1}{2}[y]^T\cdot[\Sigma]^{-1}\cdot[y]} \tag{2}$$

where $y=[y_{11}, y_{12}, \ldots, y_{MN}]^T$, and Σ is a covariance matrix of y.

In addition given image must satisfy the Markovian property:

$$P(y_{ij} \mid y_{pq}, (p,q) \neq (i,j)) = P(y_{ij} \mid y_{kl}, (k,l) \in \eta_{ij}) \tag{3}$$

The nearest pixels spatial interaction is described statistically by Gibbs distribution.

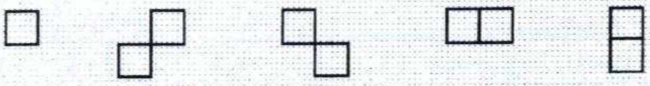
3. GIBBS DISTRIBUTION

Lets define a clique as a set of one or two neighboring pixels. Given image Y can be modeled as MRF with respect to η when and only when its joint distribution is defined according to Hammersley – Clifford theorem:

$$P(X) = \frac{1}{Z} \cdot \exp\{-U(y)\}, \tag{4}$$

where Z is a normalization constant, U(y) is an energy function value, which defines the generalized interaction of certain pixel with it's neighbors:

$$U(y_s) = \sum_{c \in C} V_C(y_s) \qquad (5)$$



a) b) c) d) e)

Fig. 1. Different cliques used in work and pixels mutual spatial location within each kind of clique. a) Single clique; b)– e) Double cliques

V_c is a potential function of type c which defines a degree of clique pixels interaction in a way of fuzzy pixels similarity evaluation. Membership function of the fuzzy relationship " y_s and y_l are similar":

$$\Phi(y_s, y_l) = \frac{|y_s - y_l|}{N} \qquad (6)$$

Two – pixel clique potential V_c is defined by value $\Phi(s,l)$, thus it is an increasing function in a closed interval $[0,\beta]$

$$V_c(y_s) = \Phi(y_s, y_l \mid l \in \eta_s) \qquad (7)$$

It corresponds to simplified fuzzy inference rule: "if pixels s and l are similar, then V_c is V". Based on the given principle the a priori probability as well as the conditional distribution defined in (1) are calculated.

A priori probability:

$$p(x_s) = \exp\{-U(x_s \sim y_t, t \in \eta_s)\} \qquad (8)$$

where

$$U(x_s \sim y_t, t \in \eta_s) = \sum_{l=1}^{7} \frac{|y_t - y_l|}{N}, \quad \forall l \in \eta_s \qquad (9)$$

Conditional on certain class probability:

$$p(y_s \mid x_s) = \exp\{-U(y_s \mid x_s \sim y_t, t \in \eta_s)\} \qquad (10)$$

where

$$U(y_s \mid x_s \sim y_t, t \in \eta_s) = \frac{|y_s - y_t|}{N} \qquad (11)$$

4. METHOD

Proposed method is baseed on neighboring pixels gradient analysis. Image clusterisation algorithm consists of several steps:

1. For extraction of homogeneous regions, the initial image is exposed tos local covariance transform using following equation:

$$\tilde{a}_{ij} = a_{ij} \cdot (1 - c_{ij}) \qquad (12)$$

where

$$c_{ij} = (q_{ij} - \mu_{ij}).(q_{ij} - \mu_{ij})^T \Big/ Norm \qquad (13)$$

q_{ij} is a row of the nearest eight neigboring to (i,j) pixels brightness values, $\mu_{i,j}$ is mean of q_{ij}. This operation pickes out all image homogenous regions (fig. 2 (b)).

2. Homogeneous regions contrast increasing is achieved by gradient correction and histogram equalization method. Unfortunately, clear histogram equalization method application not always allows us to receive desired exactness of image details. Therefore, before using the histogram equalization algorithm the image gradient correction is accomplished by:

$$b_{ij} = \tilde{a}_{ij} - \Delta a_k \qquad (14)$$

where Δa_k is a brightness difference on direction k, к=1..8:

$$\Delta a_k = a_{nm} - \tilde{a}_{ij}, \quad (m,n) \in \eta_{ij} \qquad (15)$$

It can be seen that there are eight different values of brightness gradient for each pixel. Therefore it's necessary to define the best gradient meaning according to some criterion. In this work choosing of gradient values is accomplished with famous feature detection algorithm according to entropy minimization principle (fig.2 (c)).

3. Achieved on stage 2 image is then used as initial for segmentation. Afterwards it is corrected with Bayesian segmentation method, based on MRF theory. Under classification of each pixel the following rule is used:

$$x_s = \arg\max_t P_t(X \mid Y) \qquad (16)$$

where $P_t(X|Y)$ is calculated for each of eight directions t from pixel s. During clusterisation process together with the input image two "low-pass" images found by "herringbone" algorithm of two–dimensional discrete Wavelet transformation are processed to evaluate common region forms. In this case we have deal with multidimensional version of unsupervised clusterisation based on MRF model (fig.2 (d)).

5. RESULTS

Given algorithm was tested on series of digital mammograms and on several tomographic images. Testing results show that the application of the method gives quite good results in the increasing of exactness of different medical images analysis in the sense of more accurate detail extraction and contrast improvement of the researched image object forms and borders (fig. 3). Due to clusterisation described method has a real possibility to be used as a method of suspected regions extraction before their direct recognition.

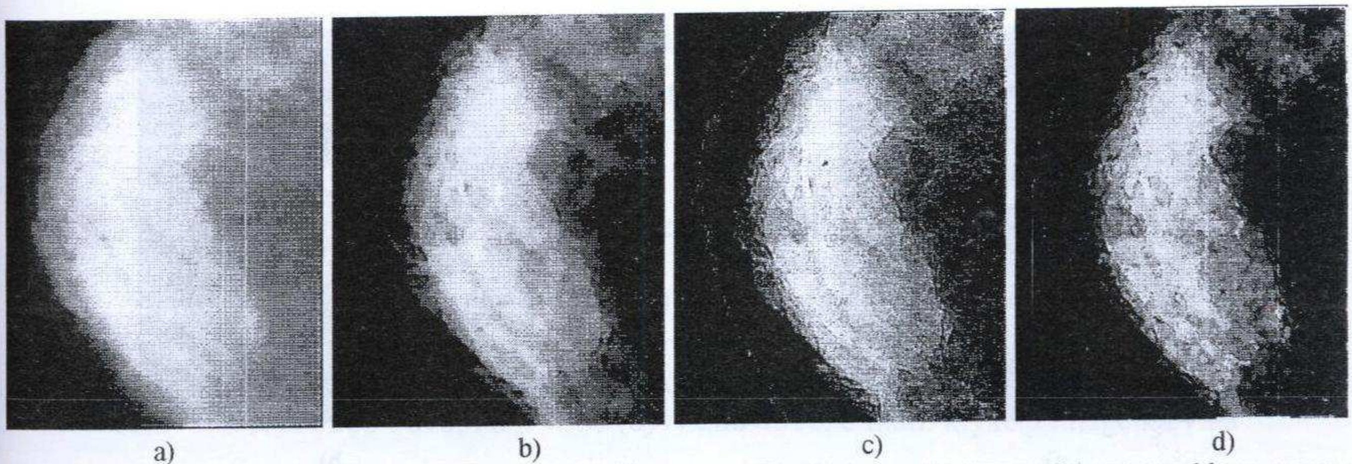


Fig. 2 Results of method application on different algorithm steps. a) Initial image; b) Image with extracted homogeneous regions; c) Image (b) after gradient correction; d) Multidimensional MAP – segmentation result with application of MRF model and Wavelet decomposition.

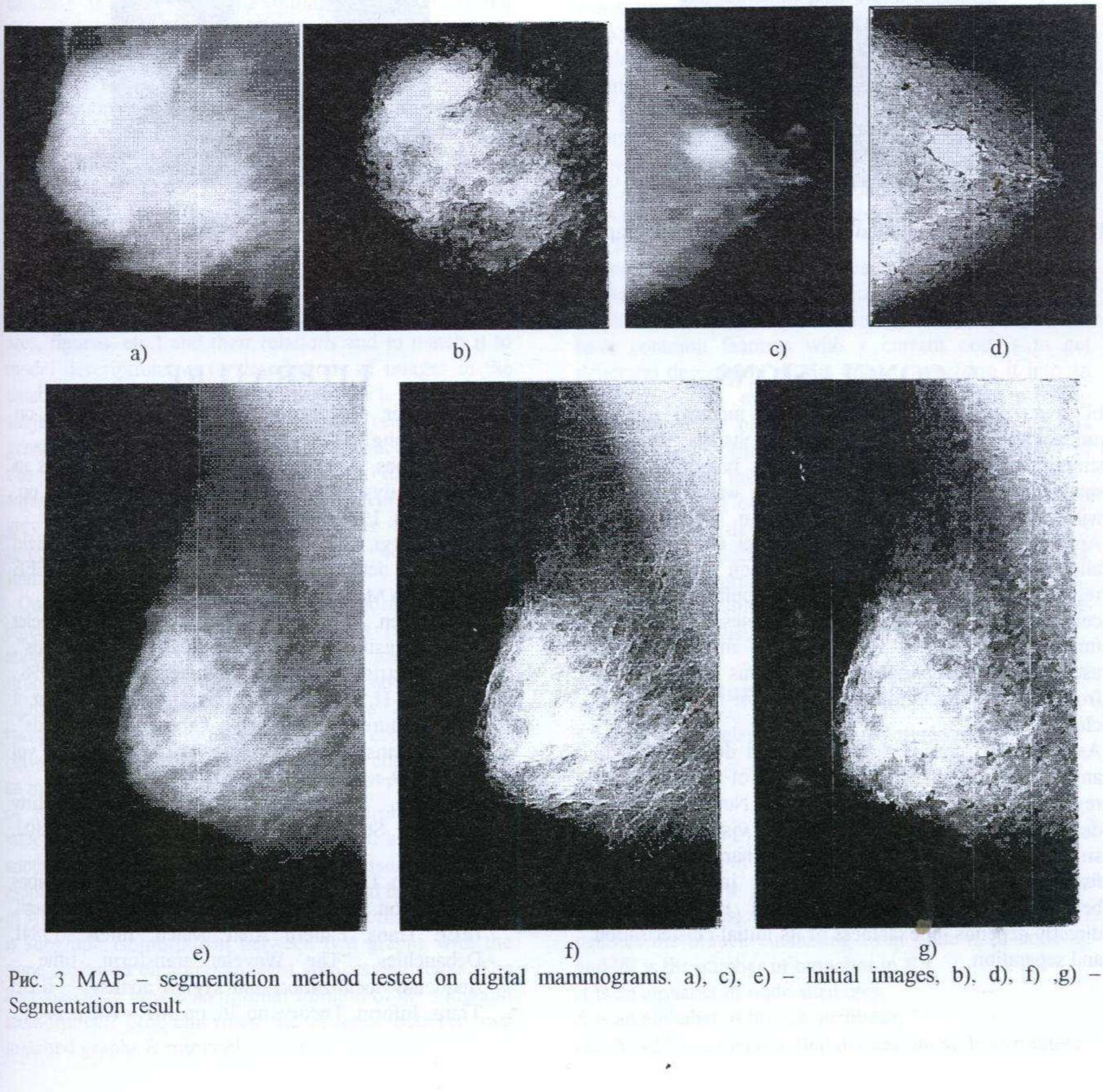


Рис. 3 MAP – segmentation method tested on digital mammograms. a), c), e) – Initial images, b), d), f) ,g) – Segmentation result.

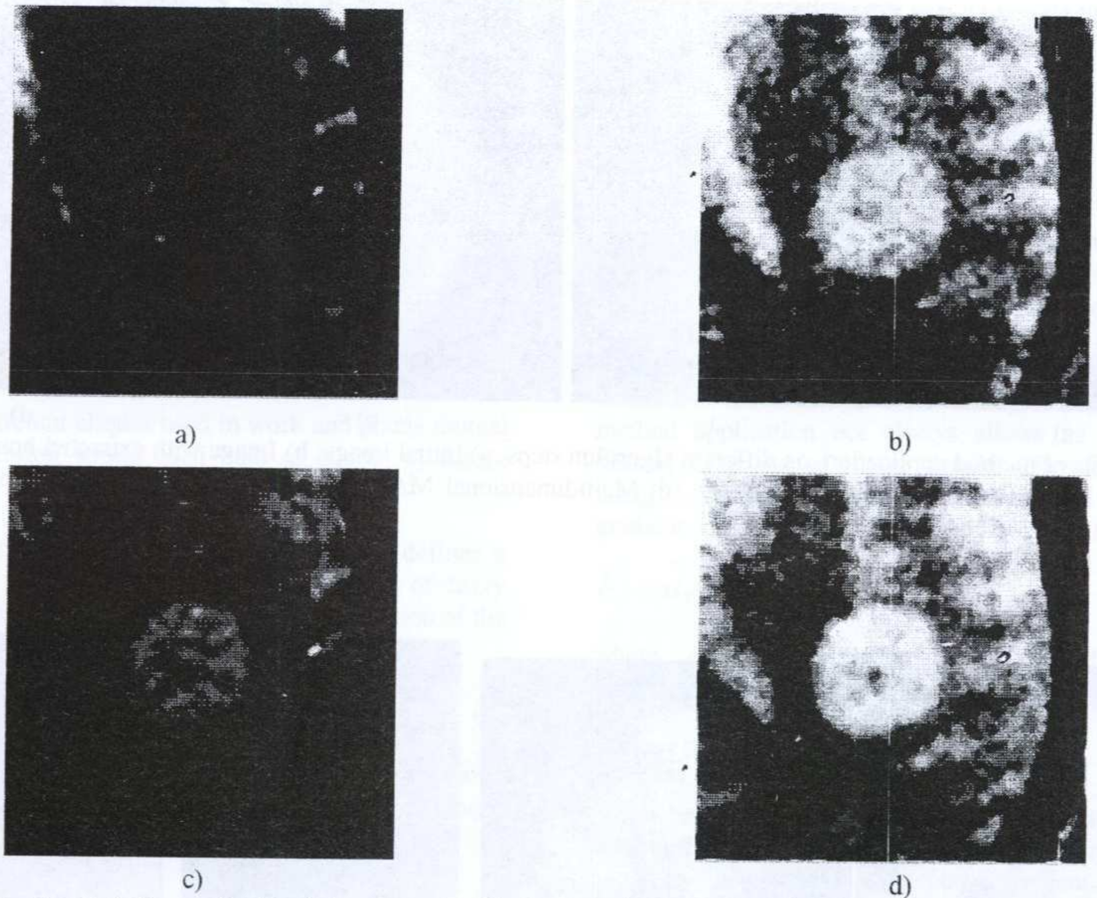


Fig.4. MAP – segmentation method tested on tomographic images. a), c) – Initial images, b), d) - Segmentation result.

6. CONCLUSIONS

In given paper we have developed medical images processing method for image visual analysis simplification. Proposed technique is based on local spatial image features analysis, whish was carried out with the help of Markov random field model. Application of multiresolution Wavelet decomposition allows us to make additional correction of segmented regions. Results of algorithm application show considerable improvement of exactness and visual image characteristics. Thus proposed method can be used in tasks of separating of suspicious tumor regions from normal background tissues for their further classification.

As it can be seen, performed method doesn't contain any classifier for the final recognition of ill and normal regions within certain medical image. Nevertheless, the described problem of image visual analysis simplification in a way of its visual characteristics and features improvement plays a very important role, because the final classification of image objects directly depends on exactness of its initial clusterisation and separation.

LITERATURE

[1] R. Kohler, "A segmentation system based on thresholding", CGIP, vol. 15, pp 319 – 338, 1981

[2] R.C. Dubes, A.K. Jain, "Random fields models in image analysis", J. Applied Stat., vol. 16, no 2, pp. 131 – 164, 1989

[3] M. Callergi, L.P. Clarke, "Markov Random Field for tumor detection in digital mammography", IEEE Trans. On Medical Imaging, vol. 14, no 3, 1995

[4] C.H. Chen, G. G. Lee, "Multiresolution wavelet analysis using gaussian markov random fields", Dep. Electrical Computer Engineering, UMD, 1998

[5] H. Derin, H. Elliott, "Modeling and segmentation of noisy textured images using Gibbs random fields", IEEE Trans. Pattern Anal. Machine Intell., vol PAMI – 9, no 1, pp 39 – 55, 1987

[6] J. Besag, "On the statistical analisys of dirty pictures", Stat. Soc., vol. 48, no 3, pp 259 - 302, 1986

[7] S. Geman, D. Geman, "Stochastic relaxation, Gibbs distribution, and Bayesian restoration of images", IEEE Trans. Pattern Anal. Mach. Intell., 1984I. Debauchies, "The Wavelet transform, time – frequency localization and sygnal analisys", IEEE Trans. Inform. Theory, no 36, pp 961 – 1005, 1981